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## Research Article

# Communication in Online Social Networks Fosters Cultural Isolation

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Online social networks play an increasingly important role in communication between friends, colleagues, business partners, and family members. This development sparked public and scholarly debate about how these new platforms affect dynamics of cultural diversity. Formal models of cultural dissemination are powerful tools to study dynamics of cultural diversity but they are based on assumptions that represent traditional dyadic, face-to-face communication, rather than communication in online social networks. Unlike in models of face-to-face communication, where actors update their cultural traits after being influenced by one of their network contacts, communication in online social networks is often characterized by a one-to-many structure, in that users emit messages directly to a large number of network contacts. Using analytical tools and agent-based simulation, we show that this seemingly subtle difference can have profound implications for emergent dynamics of cultural dissemination. In particular, we show that within the framework of our model online communication fosters cultural diversity to a larger degree than offline communication and it increases chances that individuals and subgroups become culturally isolated from their network contacts.

## 1. Introduction

A major premise of the Internet was that it would create a public sphere that fosters democratic deliberation and consensus formation [1–3]. Yet, there is increasing concern that the Internet actually reinforces processes of opinion polarization as users interact with like-minded individuals [4], a tendency that personalization algorithms installed in search engines and online social networks further intensify [5, 6]. These psychological and computational homophily biases fragment online debate into virtual echo chambers [7]. Formal models of social influence in networks are powerful tools for understanding whether and under what conditions communication in social networks fosters processes of consensus formation or opinion polarization [8]. However, existing models have been tailored to represent offline rather than online communication. Here, we show that taking into account that online communication is characterized by “one-to-many” communication rather than “one-to-one” communication drastically changes the predictions of one of the most prominent models [9]. Specifically, we show

that the one-to-many communication regime characteristic of online communication fosters the emergence of isolated individuals and the formation internally homogenous but mutually dissimilar subgroups.

Scholars have long recognized that online communication differs in important ways from its offline counterpart (see, e.g., [10, 11]), but existing research focused on differences that affect *within*-individual processes and largely ignored the complexity arising from the communication *between* individuals. A classical finding from social psychology, for instance, is that computer-mediated communication is much less affected by individuals’ physical appearance (e.g., age, gender, and ethnicity), which frees individuals from the social roles associated with memberships in high or low status groups [12]. This, it is argued, increases the relative impact that members of low-status groups have on collective dynamics, decreasing intergroup conflict and fostering consensus formation [12, 13]. Likewise, research showed that online communication allows shy individuals to overcome the communication barriers that socially isolate them in offline settings [14].

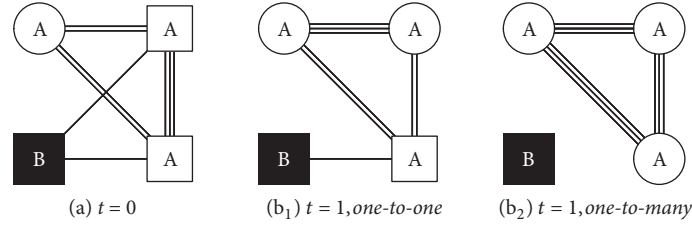


FIGURE 1: Illustration of the intuition that one-to-many communication fosters isolation. Nodes have three characteristics (color, shape, and letter) that are open to influence. The number of traits shared by two nodes and, thus, the probability that a sender exerts influence on the receiver is shown by the number of lines connecting the nodes. Panel (a) shows the initial setup before the top-left agent communicated his shape trait either under the one-to-one communication regime (Panel  $b_1$ ) or the one-to-many regime (Panel  $b_2$ ).

In contrast to the existing research, we focus on the complexity arising from the interaction *between* individuals, rather than on *within*-individual processes. To this end, we study Axelrod's prominent formal model of communication that was developed for offline social networks (and uses the one-to-one communication rule), keeping all assumptions about individual behavior unchanged but implementing communication between actors in a way that captures typical forms of online communication (one-to-many). With analytical tools and simulation, we demonstrate that this change in model assumptions drastically changes model predictions and leads to conclusions that challenge insights from research on within-individual processes. Contrary to the sketched finding that computer-mediated communication fosters the emergence of consensus [12, 13], we find that the online communication regime fosters the emergence of mutually disagreeing subgroups in our simulations. Likewise, while social-psychological research found that online communication allows some individuals to overcome social isolation [14], we demonstrate that online communication increases the chances that individuals get socially isolated. We derive these results using an approach that is very different from social-psychological research. While these studies explored how online communication changes the way individuals behave and respond to each other, our work demonstrates that differences between online and offline communication arise through merely a different communication structure. In complexity terms, we find that the “whole” changes not because the “parts” have changed but because the interdependencies between the “parts” are slightly different.

Axelrod's model of the dissemination of culture is one of the most prominent models of consensus formation and the emergence of dissimilar subgroups. It is also a typical representative of models implementing offline communication. Axelrod proposed the model to address what he perceived as a fundamental puzzle in research on social influence, asking “*If people tend to become more alike in their beliefs, attitudes, and behavior when they interact, why do not all such differences eventually disappear?*” [9, pp. 203]. Axelrod then showed with an agent-based model how assimilation at the microlevel of individual interactions can be reconciled with cultural differentiation at the level of society as a whole. Like most contributions to the literature, Axelrod's model represents individuals as nodes in a network that are described by a set of cultural traits representing individuals' cultural preferences

(like preferences for styles of music, literature, or dress). Furthermore, Axelrod implemented the so-called “one-to-one” communication regime where in a social encounter one agent always communicates one cultural trait to one of her network contacts. This one-to-one communication regime mimics the face-to-face communication present in many offline contexts, but it differs from a form of communication that is ubiquitous on the Internet and that we label “one-to-many” communication. When Internet users blog or post content on online social networks, for instance, they communicate content to multiple online contacts at once rather than to just one of them.

This paper was motivated by the following intuition about the complexity arising from one-to-many communication. Consider, for illustration, the network of four actors depicted in Figure 1(a). All actors are described by three cultural traits: shape (circle or square), color (black or white), and letter (A or B). The number of lines connecting the nodes represents the number of cultural traits the respective two nodes have in common. Implementing homophily [4, 15, 16], Axelrod assumed that trait overlap increases the likelihood that nodes will adopt a trait from their neighbor. Suppose that the top-left agent (in Figure 1(a)) communicates his shape trait under the two different communication regimes. Under the one-to-one communication regime assumed in Axelrod's model, this agent communicates his trait to one of the two agents with whom he already shares the letter and color traits. Assume that the top-right agent is selected for interaction and this agent accepted the trait. Figure 1(b) visualizes this situation, showing the increased cultural similarity between receiver and sender. As a side effect, the cultural overlap between the top-right agent and the bottom-left agent decreased, but the overall network remains connected. Figure 1(c) shows that a different outcome arises when agents communicate under the one-to-many regime. The same agent (top-left agent) communicates his shape trait, but let us assume now all actors with whom he has nonzero cultural overlap adopt the communicated trait. This has two consequences that we study in this paper. First, a culturally homogenous cluster forms, because after the communication three actors hold identical cultural traits. Communication did not only increase similarity between the sender and the receivers of the message, but also preserve the similarity between the nodes who adopted the trait. Under the one-to-one regime, in contrast, the two nodes on the right-hand side turned

less similar to each other. Second, the bottom-left agent no longer shares any trait with the other agents, ending up culturally isolated. The fact that the bottom-left agent was not influenced by the top-left agent did not only exclude that they grew more similar, but also increased the dissimilarity between the bottom-left agent and the other two agents, as they did adopt the cultural trait communicated by the top-left agent. Counterintuitively, this stylized example suggests that *cluster formation* and *cultural isolation* are more likely under the one-to-many communication regime, even though there are more instances of social influence than under Axelrod's one-to-one regime.

The intuition illustrated in Figure 1 requires a formal analysis for two reasons. First, under the online one-to-many communication regime, the sender transmitted a trait to multiple network contacts, while there was only a single act of communication under the one-to-one regime. It remains unclear whether repeated one-to-one communication could account for this apparent difference between the communication regimes or not. Second, the figure focuses on a tiny population with a simple network structure, leaving open whether one-to-many communication fosters isolation also when larger numbers of agents communicate simultaneously.

In order to test the validity of our intuition, we implemented a one-to-many communication regime in Axelrod's model of cultural dissemination, keeping unchanged all other model assumptions (thus, keeping our model "fully aligned"; [17]). That is, we included that actors simultaneously communicate a trait to their whole network at once. Subsequently, the alters decide individually whether to adopt or reject the trait according to the rules specified in the original Axelrod model. We compared the predictions of the new model with predictions of Axelrod's original model, using analytical as well as computational tools. First, we compared the two models' predictions for very small but analytically tractable social networks, conducting a Markov-Chain analysis, and find that indeed one-to-many communication increases the chances that individuals become isolated. Second, using computational methods, we show that our conclusions hold also for bigger populations, variations in the structure of the underlying social network, and higher cultural complexity in terms of the number of cultural traits and features. Moreover, we find that medium sized clusters emerge under one-to-many communication at a low, but consistent rate.

## 2. Literature

Axelrod's model of the dissemination of culture provides a prominent explanation of the emergence, diffusion, and stability of distinct cultural profiles. In this literature, an individual's culture is defined as the set of her personal characteristics (e.g., opinions, beliefs, and cultural behavior) that are susceptible to social influence [9, p. 206-7]. Cultural dynamics unfold from the conjunction of two social forces, the *selection* of culturally similar communication partners and the *social influence* resulting from communication. As social influence increases cultural similarity between communication partners, it creates in conjunction with selection a positive feedback loop that results in the emergence of

cultural clusters that grow internally increasingly similar, and, as a consequence, mutually dissimilar. Distinct cultural clusters remain stable when the cultural overlap between clusters drops to zero, which rules out subsequent communication according to the selection principle. Axelrod's model shares this critical assumption with many alternative models, such as the prominent models of bounded confidence [18, 19], as summarized in a recent literature review by Flache et al. [8].

Many contributions have extended Axelrod's work [20], testing the sensitivity of his predictions to adjustments in model assumptions about, for instance, the impact of mass media [21], institutions [22], and the scale of the cultural features [23–25]. An important advancement was the introduction of noise in the process of communication-partner selection and social influence [24, 26–28]. It turned out that allowing agents to sometimes deviate from Axelrod's assumptions with a small probability can cause the system to inevitably move towards monoculture, i.e., perfect cultural homogeneity. Model predictions are more robust, however, when agents are assumed to interact only with network contacts that share multiple cultural traits [25, 29], when network ties to contacts that are culturally too dissimilar are dissolved [30], or when agents are allowed to form institutions bottom-up that, in turn, influence the agents top-down [22]. Recently, Battiston et al. [31] conceptualized exchange discussion networks as a multiplex system in which different topics are discussed among different peers. Multiple disseminations of culture models are layered on top of each other, creating distinct and robust clusters of cultural identities.

Another extension to the model that can explain the persistence of cultural diversity despite random deviations is the so-called "multilateral social influence" [32], a form of social influence that is similar to the concept of "complex contagion" from the literature on diffusion processes in social networks [33]. Unlike Axelrod, who modeled influence as a dyadic, one-to-one process where an agent adopts a cultural trait from a network contact, Flache and Macy [32] assumed that agents always consider the cultural traits of multiple network contacts when they reconsider their cultural profile and adopt the trait that dominates in their neighborhood. This "many-to-one" form of cultural communication makes predictions much more robust to noise and is the reverse of the "one-to-many" communication regime that we study here. That is, while Flache and Macy assumed that an agent is always influenced by multiple network contacts, we consider that an individual agent exerts influence on multiple contacts.

Modelers have also incorporated assumptions about one-to-many communication in existing models [34, 35]. However, while there are social influence models that implement communication regimes similar to the one-to-many communication that we study, the literature lacks an analysis of whether and under what conditions one-to-many communication generates different cultural dynamics compared to one-to-one communication. Thus, unlike earlier contributions, we implement one-to-many communication in Axelrod's model keeping all other model assumptions unchanged. Next, we compare predictions of the new model with the predictions of the original approach.

TABLE 1: Basic assumptions of the dissemination of culture model with one-to-one communication and our implementation with one-to-many communication.

|                                  | One-to-one communication   | One-to-many communication  |
|----------------------------------|--|--|
| (1) Select active agent $i$      | Every time step $t$ pick an agent $i$ from the population <sup>1</sup>   | Every time step $t$ pick an agent $i$ from the population  |
| (2) Select communication partner | Pick a neighbor $j$ of agent $i$   | (not needed)   |
| (3) Select communicated trait    | Pick a feature $f$ on which $i$ and $j$ differ ( $q_{if} \neq q_{jf}$ )  | Pick a feature $f$ on which $i$ and at least one neighbor $j$ differ ( $q_{if} \neq q_{jf}$ , for any $j$ )  |
| (4) Homophilous social influence | With a probability $p_{ij}$ equal to the proportion of traits that $i$ and $j$ share ( $q_{if} = q_{jf}$ over $F$ ), let $j$ adopt trait $q_{if}$ from $i$ | With a probability $p_{ij}$ equal to the proportion of traits that $i$ and $j$ share ( $q_{if} = q_{jf}$ over $F$ ), let each neighbor $j$ adopt trait $q_{if}$ from $i$ |

<sup>1</sup>In the original model, Axelrod describes influence to go from  $j \rightarrow i$ , but in order to make the formalization of one-to-one and one-to-many communication comparable, we change the phrasing of influence to go from  $i \rightarrow j$ . The two implementations are mathematically equivalent.

### 3. The Model

The aim of the present analysis is to test our intuition that one-to-many communication generates more isolation than one-to-one communication. To this end, we compare the predictions of Axelrod’s prominent model of cultural dissemination, which assumed one-to-one communication, with a novel extension of the same model that captures one-to-many communication. Like in the original Axelrod model, we generate populations of  $N$  agents. Every agent has a cultural profile, a vector  $C_i$  with  $F$  nominal features with  $Q$  possible traits. Features represent cultural attributes that are open to social influence, and traits refer to the distinctive content of a feature for a given agent. Formally,

$$C_i = (q_{i1}, q_{i2}, \dots, q_{iF}), \quad q_{ix} \in \{0, 1, \dots, Q-1\} \quad (1)$$

Axelrod’s used a very abstract representation of agents’ cultural characteristics. Features can represent something as basic as the person’s favorite song or something as complex and multidimensional as the person’s music taste. Likewise, it can model the person’s view on abortion or her much more complex preference for a specific political party which may be a function of her view on abortion and many other aspects. In Section 4.2.6, we study how the dynamics emerging from one-to-one and one-to-many communication are affected by cultural complexity measured in terms of the number of features and traits per feature.

Table 1 summarizes and compares the two variants of Axelrod’s model. At every time step  $t$ , an agent  $i$  is selected at random from the population. This agent is the source of influence. Second, in the original model, one of  $i$ ’s neighbors is selected for communication with  $i$ , a step that is not necessary under one-to-many communication where  $i$  communicates with all of her neighbors who are open to influence and not yet culturally identical. In Step (3), one of the cultural features on which there is not yet consensus between agent  $i$  and her neighbors is selected. In Axelrod’s original model, this translates into the exclusion of all features where  $i$  and  $j$  hold the same trait. In the variant with one-to-many communication, however, one of the features where  $i$  disagrees with at least one of her neighbors is picked. Unlike

in Axelrod’s model with one-to-one communication, this implies that  $i$  might transmit a trait to one of her neighbors  $j$  that  $j$  already adopted, making this dyadic communication ineffective. However, similar to Axelrod’s model, also the variant with one-to-many communication excludes that a feature is chosen in which cultural change is impossible, as there must be at least one neighbor who disagrees with  $i$  on the selected cultural dimension. Step (4) implements social influence and is, therefore, the part where one-to-one and one-to-many communication are implemented. In Axelrod’s original model, actor  $j$  adopts the selected trait with a probability equal to the overall cultural overlap between  $i$  and  $j$ . For instance, when  $i$  and  $j$  hold the same trait on half of the features, then the chance that  $j$  will adopt the trait chosen in Step (3) is 50 percent. This implements homophily, the notion that individuals tend to be influenced by like-minded communication partners. Empirical research showed that homophily is a strong force both online and offline [4, 36, 37]. The same principle is implemented in the new version of the model but here every neighbor of  $j$  adopts the selected trait with a probability equal to the pairwise cultural similarity between  $i$  and the respective neighbor  $j$ .

### 4. Comparison of the Two Communication Regimes

We compared the models with two different methods. First, we studied small populations of only four agents described by only three dichotomous cultural features. The simplicity of this setup allowed us to conduct a detailed analysis and provide an analytical proof using a Markov-chain analysis. Second, we conducted agent-based simulations in order to test whether the conclusions from the Markov-chain analysis also hold in more complex settings with more agents, higher numbers of cultural traits and features, different neighborhood sizes, and more complex network structures. Using a larger population size in the second analysis also allowed us to address what Axelrod was primarily interested in, cultural diversity. More precisely, we could test in the second analysis how the communication regime affects the degree of and conditions for cultural clustering, the coexistence of



|   |   |   |
|---|---|---|
| $\begin{pmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix}$ | $\begin{pmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$ | $\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}$ |
| (a)   | (b)   | (c)   |
| Symmetrical   | Semi-   | Non-  |
| (13-13-13s)   | symmetrical   | symmetrical   |
|   | (13-13-13ss)  | (13-13-13ns)  |

FIGURE 2: Example states of the 13-13-13 classes, traits on features (rows) by agents (columns).

local consensus, and global diversity highlighted by Axelrod's original analysis.

**4.1. Markov-Chain Analysis.** To be able to compare the two models with analytical tools, we first analyzed a setting that is very simple but where the intuition outlined above, nevertheless, suggests that predictions of the two model variants differ. According to the described intuition, isolation in the one-to-many model might arise when an actor  $j$  is not influenced by a network neighbor  $i$ , but their joint neighbors are influenced. Clusters form because an actor  $j$  exerts the same influence on multiple network contacts. Testing this intuition requires a network consisting of sender  $i$ , receiver  $j$ , and at least two other receivers  $k$  and  $l$ , that is fully connected. Furthermore, we set the number  $F$  of cultural features to 3, as this creates sufficient variation in probability that agents influence each other. If two agents do not share a trait on any of the three features, their communication probability  $p_{ij} = 0$ . If they share 1 trait, then  $p_{ij} = 1/3$ . If they share 2 traits, then  $p_{ij} = 2/3$ ; and if they share all traits,  $p_{ij} = 1$ . Finally, we assumed that all three features are dichotomous ( $Q = 2$ ).

The system with  $N = 4$ ,  $F = 3$ , and  $Q = 2$  has a finite number of cultural configurations. A cultural configuration is a mapping that assigns to each of the  $F$  features of each of the  $N$  agents a value from the set of possible trait values (0 or 1). The total number of possible configurations is  $Q^{FN} = 2^{12} = 4096$ .

The dynamics of this system can be fully represented as a Markov chain that assigns to every ordered pair of cultural configurations a probability to move from one configuration to the other within one iteration of the simulation of the model. With 4096 configurations this Markov model of the system is prohibitively large for an exhaustive analyses. However, we can partition the set of all configurations into subsets, called *classes* hereafter, which have the property that for every ordered pair of configurations  $X$  and  $Y$  of which  $X$  falls into class  $S_1$  and  $Y$  falls into class  $S_2$ , the transition probability from  $X$  to  $Y$  is the same. Analyzing the dynamics of the Markov Chain constituted by these classes and transition probabilities between them is equivalent to analyzing the Markov Chain of all configurations. As we will show, we can reduce the system to a number of classes that is small enough to derive analytically the probabilities that cultural isolation arises from a random start under one-to-one and one-to-many communication, respectively.

To arrive at a partition of the configurations into classes, we first observe that each feature  $f$  is always in exactly one of the three different states.

**Consensus.** All agents adopt the same trait on feature  $f$ . According to Rule 3 of both models, any future communication changing this feature is excluded because consensus has been reached.

**1-3 Split.** One agent adopted trait  $q$ , while the three others have  $q'$ .

**2-2 Split.** Two agents share trait  $q$ , while the other two agents adopted  $q'$ .

A first classification of configurations can be obtained from distinguishing configurations that have a different distribution of states over the three features. All configurations that have the same number of features in the states C (consensus), 13 (1-3 split), or 22 (2-2 split) fall into the same semi-class. The number of distinct semi-classes can be obtained from computing the number of possible outcomes if for every feature its state is drawn randomly and independently with replacement from the three possible values C, 13, or 12. Thus, for the case where a feature can be in  $r = 3$  different states and there are  $n = 3$  features constituting a cultural vector, this number is given as the number of unordered permutations for a set when sampling with replacement as

$$\frac{(r + n - 1)!}{r! (n - 1)!} = \frac{(3 + 3 - 1)!}{3! (3 - 1)!} = 10 \quad (2)$$

However, a semi-class can consist of several classes; thus the number of classes is larger than 10. The reason is that transition probabilities from a configuration containing features with more than one 1-3 split or 2-2 split may be different, depending on whether the splits separate the set of agents along the same lines or are asymmetrical. We distinguish three degrees of symmetry within the semi-classes with more than one nonconsensus feature and assign the labels: symmetrical (s), semi-symmetrical (ss), or non-symmetrical (ns).<sup>1</sup>

For example, the 13-13-13 semi-class (i.e., all three features contain a "1-3 split") consists of three different classes: symmetrical, semi-symmetrical, and non-symmetrical. Examples are shown in Figure 2. Even though the three configurations are part of the same semi-class, they have very different probabilities of communication and transition into another class. The symmetrical 13-13-13 class (13-13-13s) is an absorbing state of the dynamic and is characterized by one cluster of three culturally identical agents and one isolate. The isolated agent in this class is different from the same three others on all three features, and thus no further communication is possible. The configurations 13-13-13ss and 13-13-13ns shown

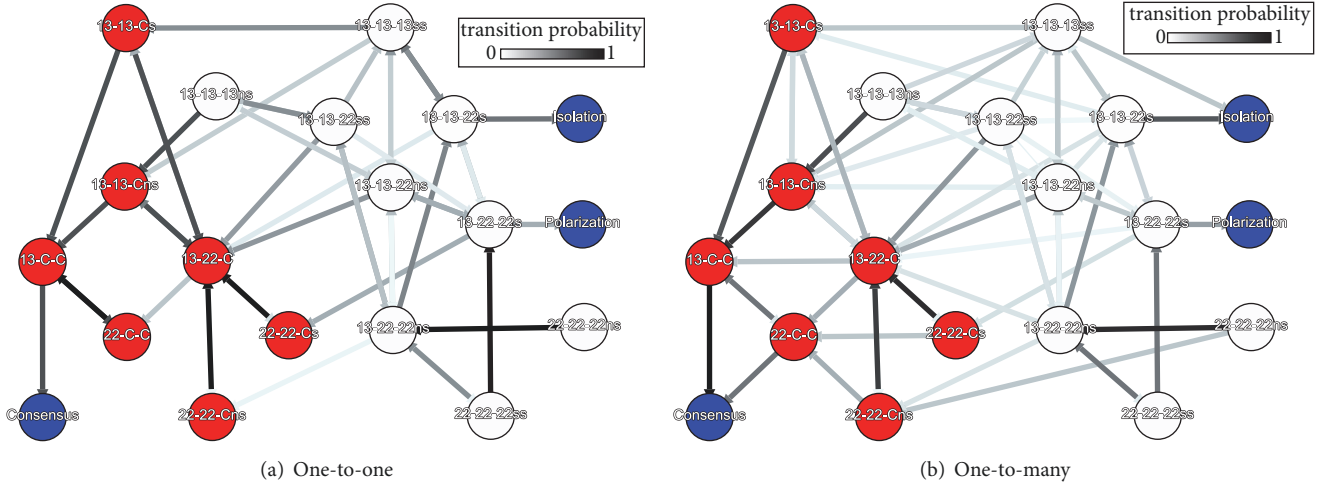


FIGURE 3: Markov chains for the one-to-one and one-to-many communication regimes in the  $N = 4, F = 3, Q = 2$  model. Nodes represent classes and the directed edges are colored according to between-class transition probabilities. Blue nodes are absorbing classes, red nodes are classes from which consensus is the only reachable equilibrium, and white nodes indicate that from there multiple equilibria are still reachable.

in Figure 2 instead allow for communication between some or all agents. An overview of all classes and the proportion of states that fall into each class is included in Appendix A.

For both model variants, one can identify a partition into a small number of classes of configurations and calculate for every pair of classes the probability that the corresponding transition occurs within one iteration. Figures 3(a) and 3(b) visualize the transition probabilities for both models variants. In the figures, nodes are colored according to whether they represent an absorbing class (blue), a class from which consensus is the only reachable equilibrium (red), or whether more equilibria are still reachable (white).<sup>2</sup> Edge color corresponds to the probability that the system moves from one state to another with darker edges indicating higher transition probability. Recursive paths (self-loops) are not shown.

Both model variants have three possible absorbing classes; these are classes that once selected by the dynamics will never be left again: the consensus class (C-C-C), the isolation class (13-13-13s), and the polarization class (22-22-22s). Consensus is stable since social influence will never lead to changes in agents' features. Isolation and polarization are group split states; they are stable because actors are either perfectly similar or perfectly dissimilar from their neighbors. In both cases, communication will never lead to changes in the cultural features. As can be seen in the transition diagram, as well as in the transition matrix diagonal, these are the only classes that are "sinks" with an out-degree of zero in the Markov graph. Given that from every other class there is path towards at least one of the absorbing classes, we know that in the long run the system must end up in one of the absorbing classes.

Figure 3 illustrates how isolation can more readily emerge under one-to-many communication. For example, once the system has reached a configuration in which one agent is "almost" isolated but still agrees with the three others on one single feature (13-13-22s, upper-right corners of Figures 3(a) and 3(b)), it is under one-to-many communication three

TABLE 2: Stationary distributions for the  $N = 4, F = 3, Q = 2$  model with two communication regimes.

| Class                             | Communication regime |             |
|-----------------------------------|----------------------|-------------|
|                                   | One-to-one           | One-to-many |
| C-C-C ( <i>consensus</i> )        | .801                 | .713        |
| 22-22-22s ( <i>polarization</i> ) | .064                 | .073        |
| 13-13-13s ( <i>isolation</i> )    | .135                 | .215        |

times as likely that this agent will end up isolated after the next influence than it is under one-to-one communication.<sup>3</sup> More generally, using the Markov chain convergence theorem, one can calculate for each of the three absorbing classes the probability to be reached under both communication regimes, given the initial distribution of configurations. This requires a row vector  $q$  of the initial distribution of states and the transition matrix  $T$ . The stationary distribution  $p^*$  is then given by

$$p^* = qT^{\infty} \quad (3)$$

Table 2 reports the stationary distributions for both model variants given a uniform probability of initializing the system in any of its 4096 configurations. These results support our intuition that isolation is a more likely outcome of the dynamics of cultural influence under the one-to-many communication regime than under the one-to-one communication regime. More precisely, we find that the probability of the outcome of cultural isolation is about 1.6 times higher under one-to-many communication (.215 versus .135). We also observe that one-to-many communication reduces the likelihood of consensus to emerge and thus increases the likelihood that cultural diversity persists despite social influence. Next, we turn to exploring how one-to-many communication affects the likelihood and persistence of isolation and cultural clustering in larger populations.

**4.2. Isolation and Cultural Clustering in Bigger Populations.** The Markov-chain analysis supported our intuition that isolation and polarization are more prevalent in the one-to-many communication regime. However, with only 4 agents, we can not distinguish polarization (separation in exactly two culturally opposed subgroups) from cultural clustering into a larger number of distinct local clusters. To test whether and under which conditions our analytical finding is robust and generalizes to cultural clustering also in larger networks, we conducted computational experiments with bigger populations, always starting from a random initial assignment of traits and 1,000 independent replications per experimental condition. All simulations were executed until dynamics had reached an equilibrium.

In the following subsections, we first compare one-to-one and one-to-many communication in three different network configurations. First, we focused on a regular torus network, as this is the framework that Axelrod used (Section 4.2.1). Second, we compared the two communication regimes in ring networks with different degrees of network transitivity, in order to test whether the micro-level intuition illustrated in Figure 1 is indeed responsible for the macro differences that we observe in bigger populations (Section 4.2.2). Using the ring networks, we also varied the size of the agents' neighborhoods to test whether or not cultural clustering and isolation persist when individual's communication networks grow bigger under one-to-many communication (Section 4.2.3). Next, we studied spatial random graphs, as these networks have been argued to mimic human social networks better than torus networks and ring networks (Section 4.2.4). Subsequently, we describe ideal-typical simulation runs under one-to-one and one-to-many communication to illustrate differences (Section 4.2.5) and replicate our main findings for populations consisting of agents with more features ( $F$ ) and a higher number  $Q$  of possible traits per feature.

**4.2.1. Population Size Effects.** There are at least two reasons for increasing the number of agents in the model. First, already Axelrod found that monoculture (perfect cultural consensus) is virtually unavoidable once population size exceeds a critical threshold [9, pp. 214-5], because dynamics last longer in bigger populations. This increases chances that two subgroups A and B that have grown maximally dissimilar at some moment restart communication because one agent adopted a trait from a third subgroup C that increased cultural similarity between A and B. This finding raises the question whether the differences between the two communication regimes persist when bigger populations are assumed. Second, the aim of the present analysis is to contribute to the development of a valid representation of online communication, a setting where huge numbers of individuals interact.

Manipulating the communication regime whilst keeping all remaining characteristics of Axelrod's model unchanged, we first compared the two models in the same cellular-world structure that Axelrod assumed in his seminal work and that many follow-up studies adopted (e.g., [9, 26, 32]). That is, we assumed that  $N$  agents are distributed over a wrapped square lattice (a torus) such that every agent occupies one cell. All agents are linked to their neighbors in the so-called

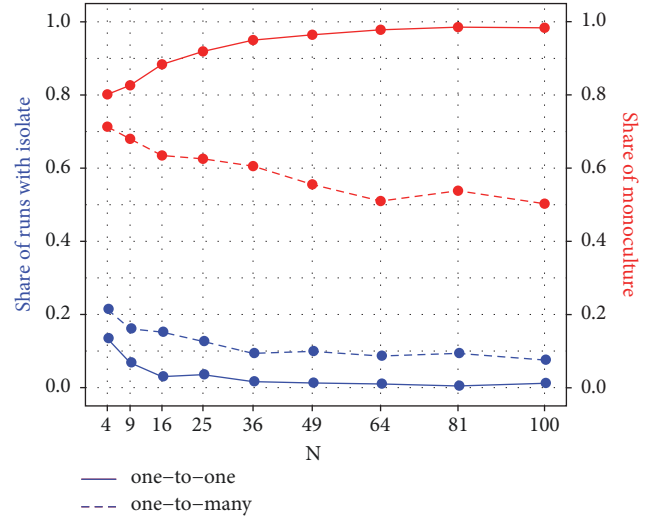


FIGURE 4: Effect of population size  $N$  on the share of runs with at least one isolate (blue lines), and share of runs characterized by monoculture (red lines) in a torus network with  $F = 3$ ,  $Q = 2$ , 1,000 replications per condition, measured at equilibrium.

“Moore neighborhood” and can thus interact with eight other agents.<sup>4</sup> The first simulation experiment focused on populations characterized by a torus network and agents with three cultural features with two possible traits. To study population-size effects, we created populations with  $m^2 = N$  agents and varied  $m$  between 2 and 10. In Appendix B, we show that our findings are robust when  $m$  is increased to 30 which translates into populations of 900 agents.

Figure 4 compares the two communication regimes in terms of the share of runs that ended with at least one isolated agent. An isolate is defined as an agent that is maximally different from all of her network contacts. The blue lines show that isolation still occurs under one-to-many communication even in larger populations, while isolation virtually disappears in the one-to-one regime. Under the one-to-many regime, isolation is most likely in very small populations, but once population size exceeds 36, the model with one-to-many communication generates a constant share of about 12 percent of the runs that are characterized by isolation. This finding was confirmed by simulations with populations of 900 agents ( $m = 30$ ; see Appendix A).

Figure 4 furthermore shows that the proportion of runs that end in monoculture (see the red lines) decreases with  $N$  under one-to-many communication, while the share of runs generating monoculture increases in population size under the original model. Axelrod already found that the original model implies more monoculture in larger populations [9], a result that generalizes to various extensions of the model (e.g., [26, 30]). Axelrod deemed this a counterintuitive finding, confronting it with contradictory empirical evidence from a study of language diversity on islands in the South Pacific, which found that there is more language diversity on larger islands. Our results here suggest that one-to-one communication plays an important role in the generation of Axelrod's counterintuitive finding. In his original model, dynamics



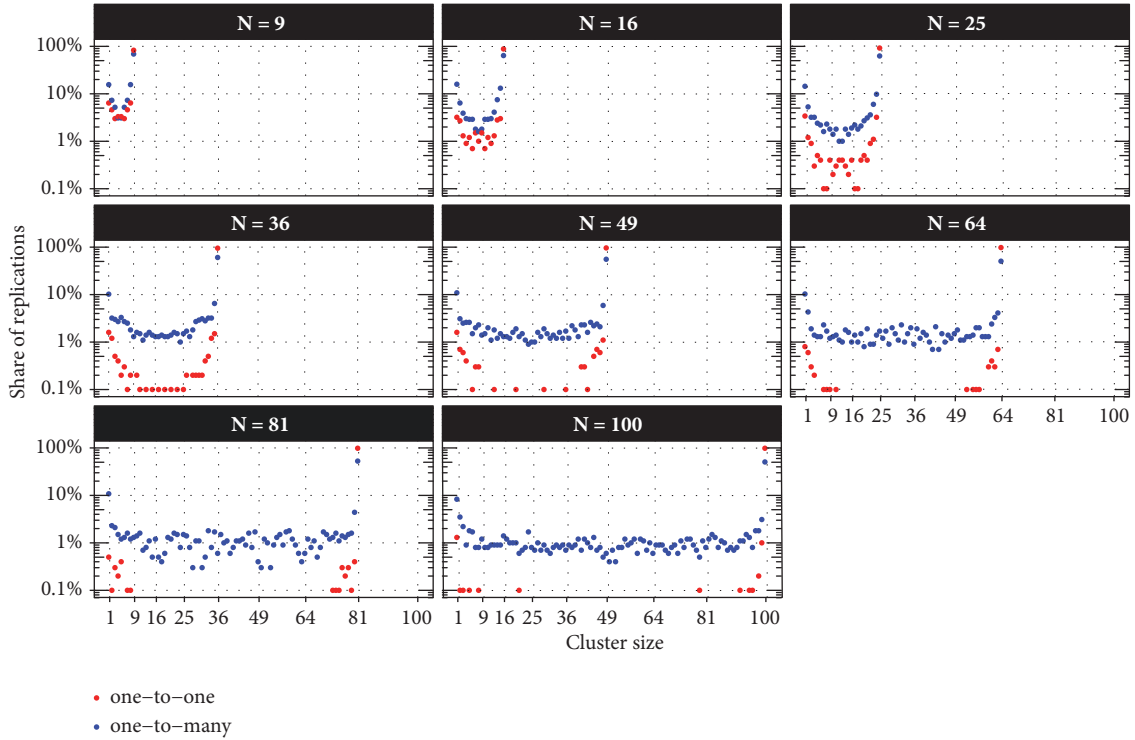


FIGURE 5: The share of replications that contain a given cluster size by  $N$  and interaction regime. All replications in torus network with  $F = 3$ ,  $Q = 2$ , 1,000 replications per condition.

generate monoculture in big populations because whenever a culturally homogenous region begins to form, the emerging local consensus can be disrupted by a single communication event of one member of the region with an outside source of influence. In large populations, these disruptions are more likely, simply because dynamics last longer than in small populations. Such outside influences are also possible under one-to-many communication. However, the main difference is that one-to-many communication offers many more possibilities how a “deviant” is reached by influences from members inside of the emergent region to which the deviant belongs. In Axelrod’s original model, the algorithm always randomly picks two communication partners  $i$  and  $j$  (see Steps (1) and (2) in Table 1), which implies that the chance that a deviant  $j$  is influenced back by a neighbor who belongs to the cultural region is only  $1/8$  in a population with Moore neighborhoods. With our implementation of one-to-many communication,  $j$  will always be targeted by  $i$ , as  $i$  exerts influence on all neighbors. This greatly increases the robustness of cultural regions. Further support for this interpretation is given by similar findings that Flache and Macy [32] obtained with a model assuming many-to-one communication.

To test whether one-to-many communication fosters not only isolation but also the formation of clusters, Figure 5 shows how population size affects the relative frequency of clusters of different sizes. Even though clusters of size one and size  $N$  are consistently the most likely outcome to be generated by the model, there is a remarkable difference

between the two communication regimes. Under one-to-one communication, the occurrence of “medium sized” clusters (those larger than one and smaller than  $N$ ) diminishes as  $N$  increases, whereas one-to-many communication does generate clusters of all different sizes at all levels of  $N$ . In the simulation runs with  $N = 100$ , for example, we found that with one-to-one communication 1.2% of the replication runs end with at least one isolate and 1.6% of the runs generate medium sized clusters. Under one-to-many interaction, the proportion of runs with at least one isolate rises to 7.7% and medium sized clusters appear in equilibrium for 49.4% of the runs. Moreover, these medium sized clusters seem to emerge at a similar rate. Any given cluster size between 2 and 99 has an average probability of exactly 1.00% (SD = 0.46%) to appear in a given run (compared to 0.02% under one-to-one interaction). This demonstrates how one-to-many communication stabilizes cultural diversity and clustering. Both communication regimes typically generate cluster size distributions with peaks at both ends of the scale (at cluster size one or  $N$ ). Independent of population size, however, one-to-one communication generates more monoculture, less isolation, and less clustering than one-to-many communication.

Figure 6 informs about the effect of the communication regime on the relative size of the biggest subgroup in the population ( $S_{max}/N$ ), a standard outcome measure in the literature. The figure shows that the few runs with bigger populations under the one-to-one regime that did not end

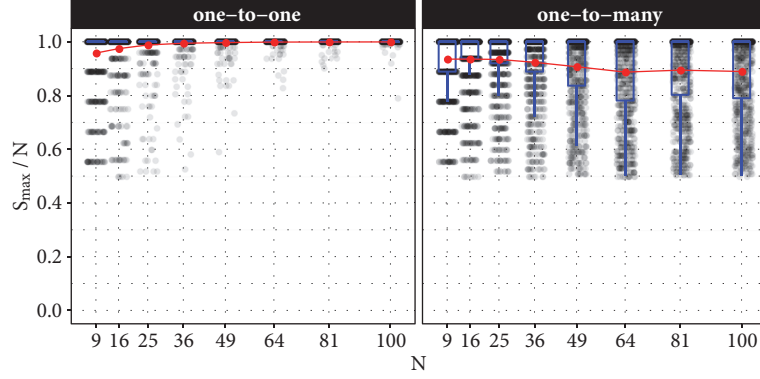


FIGURE 6: Homogeneity after convergence in a torus network with  $F = 3$  and  $Q = 2$  by population size  $N$  and communication regime. Boxplots are shown in blue and averages indicated with red marks. 1,000 replications per condition.

in monoculture were always characterized by one very big cluster. Under one-to-many communication, the size of the biggest subgroups can be much smaller, in contrast.

#### 4.2.2. Effects of Network Transitivity on Cultural Diversity.

Figure 1 illustrates a key element in our reasoning why one-to-many communication fosters both isolation and clustering. According to our intuitive argument, one-to-many communication generates isolation and cluster formation when an agent is *not* adopting a trait from a network contact but their joint network contacts do adopt the trait and, therefore, grow similar to each other and dissimilar to the agent who was not influenced. Such a series of events can only occur, however, when the sender and the agent that becomes isolated have common friends. In other words, a high degree of transitivity in the sense that many network triads are closed (actor  $a$  is connected to  $b$ ,  $b$  is connected to  $c$ , and  $c$  is connected to  $a$ ) can be expected to contribute to both cultural clustering and isolation and amplify the difference between the regimes. To test whether transitivity is indeed responsible for the differences between the two communication regimes, we compared populations characterized by different degrees of network transitivity.

We replicated parts of the analyses presented in the previous section, manipulating the degree of transitivity in the population's social network.<sup>5</sup>

In this simulation experiment, we focused on populations of 100 agents ( $N = 100$ ) holding three features ( $F = 3$ ) that could adopt two traits ( $Q = 2$ ). To manipulate the average transitivity in the network, we created symmetric ring networks where agents were connected to the four closest neighbors to the right and to the left [38]. In the resulting network, all agents had the same degree ( $k = 8$ ), just as in the simulations with the torus network. Furthermore, the network was characterized by a very high degree of transitivity, as connected agents tend to be connected to the same nodes (transitivity in this network is 0.64). Next, we rewired network links following the algorithm proposed by Maslov and Sneppen (2002), which decreases network transitivity while preserving the degree distribution. The Maslov-Sneppen rewiring algorithm first picks two edges

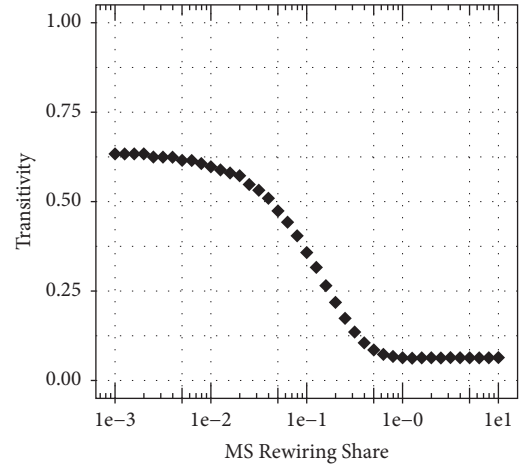


FIGURE 7: Average transitivity by share of Maslov-Sneppen rewiring. Observed in Watts-Strogatz graph with  $k = 8$  for  $N = 100$ , 100 replications per condition.

$A \longleftrightarrow B$  and  $C \longleftrightarrow D$ , making sure that  $A \notin \{C, D\}$  and  $B \notin \{C, D\}$  and that  $A \nleftrightarrow D$  and  $B \nleftrightarrow C$ . If any of these conditions is not met, a new pair of edges is picked. Otherwise, the algorithm removes the links  $A \longleftrightarrow B$  and  $C \longleftrightarrow D$  and adds  $A \longleftrightarrow D$  and  $B \longleftrightarrow C$ . This procedure is repeated until the algorithm has successfully rewired a share  $R$  of the total number of edges in the graph. We studied the two communication regimes for different shares  $R$  of Maslov-Sneppen rewiring, namely,  $R = \{10^{-i/10}\}_{i=-30}^{10}$ . Figure 7 visualizes how the share of rewired links translates into network transitivity. Transitivity is defined as the share of closed triplets in the network or, formally,

$$\text{Transitivity} = \frac{3 \times \text{number of closed triangles}}{\text{number of triplets}} \quad (4)$$

Figure 8 depicts the association between transitivity and the relative size of the biggest subgroup in the population. The box plots show that, under the one-to-one communication regime, network transitivity is not meaningfully related to the outcome measure. In contrast, the bottom panel of

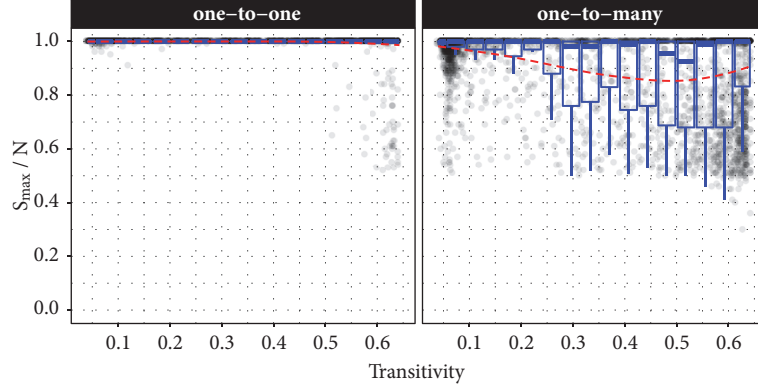


FIGURE 8: Homogeneity after convergence in a Watts-Strogatz network with  $N = 100$ ,  $F = 3$ , and  $Q = 2$  by degree of transitivity and communication regime. Boxplots are shown in blue with bin width set to 0.037 and a Loess curve is shown in red. The graph with 100 replications per experimental condition, but networks with transitivity values between 0.15 and 0.5 are less frequent as Figure 7 shows.

the figure shows a strong association under the one-to-many communication regime. This supports our conjecture that one-to-many communication fosters cultural clustering only in networks characterized by a sufficient amount of transitivity. Note that the scatter plots on the very left and on the very right of the figure represent more simulation runs, as the used rewiring algorithm generates more networks with very high and very low transitivity (see Figure 7).

**4.2.3. Varying Neighborhood Size.** So far, we have studied networks where all agents had a degree ( $k$ ) of eight, because this resonates with Axelrod's work. However, we also tested whether one-to-many communication fosters cultural isolation also when agents have more than eight network contacts. To this end, we studied populations of 49 agents interacting in ring networks as described in Section 4.2.2. Agents were described by three features and two traits per feature. To study effects of agents' degree, we varied the number  $k$  of neighbors from 2 to 48 in steps of (2), conducting 1,000 independent replications per condition. Thus, under  $k = 2$  the network was a perfect ring where every agent had one neighbor to the left and one to the right. Under  $k = 4$ , agents were connected to the two closest neighbors to the right and to the left, and so on. A degree of  $k = 48$  implemented a complete graph.

Figure 9 informs about how agents' degree affected how often we observed cultural isolation or monoculture under the two communication regimes. In line with Axelrod's work, the solid lines show that under the classical one-to-one communication dynamics tend to generate monoculture when agents have bigger neighborhoods. The figure shows only a small difference between the two communication regimes in very sparse networks ( $k = 2$ ), which supports our conjecture from Section 4.2.2 that network transitivity is a necessary requirement for generating more cultural clustering under one-to-many communication. A ring network with  $k = 2$  is a periodic line network with zero triplets. As a consequence, rejecting a trait communicated by a neighbor does not make agents more dissimilar from their other neighbor, which implies that the mechanism responsible for isolation under one-to-many communication (see Figure 1) is not activated.

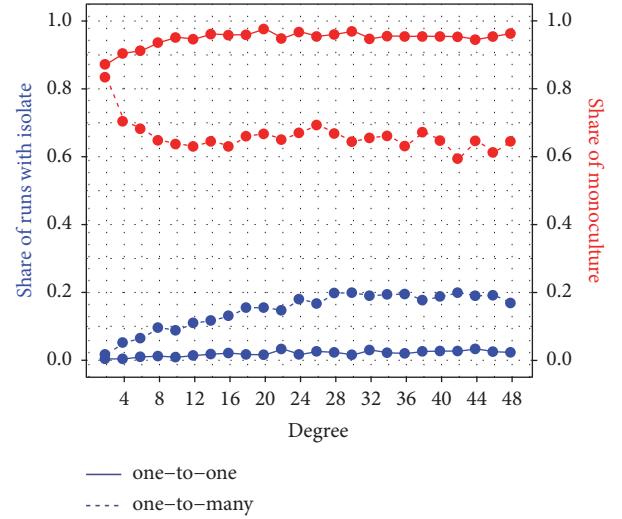


FIGURE 9: Effect of degree  $k$  on the share of runs with at least one isolate (blue lines), and share of runs characterized by monoculture (red lines) in a Watts-Strogatz graph with  $N = 49$ ,  $F = 3$ ,  $Q = 2$ , 1,000 replications per condition.

In contrast, Figure 9 shows stark differences between the two communication regimes when agents have bigger network neighborhoods. Unlike Axelrod's original model, the model with one-to-many communication predicts that monoculture is less likely when degree is increased. As  $k$  increases, also the number of closed triads in the network rises, which sets into motion the isolation mechanism. As a consequence, the proportion of runs ending in monoculture drops to about 0.65 under one-to-many communication. In about half of the simulation runs with a high degree that did not end in monoculture, there was at least one isolate.

Figure 10 illustrates how degree affected the relative size of the biggest cultural cluster in the network. Under one-to-many communication, the average size of the largest cluster decreases as degree rises from 2 to 8. However, the average cluster size rises again when degree is increased further.

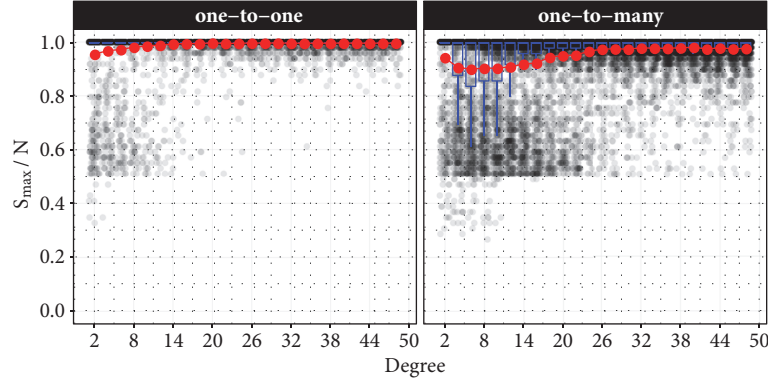


FIGURE 10: Effect of degree on relative size of the biggest cultural cluster in a Watts-Strogatz graph with  $N = 49$ ,  $F = 3$ , and  $Q = 2$  by degree and communication regime. Boxplots are shown in blue. Averages are shown with red marks. 1,000 replications per condition.

Nevertheless, even when agents have very high degree, there remains a noticeable difference between one-to-one and one-to-many communication. We believe that the non-monotone effect of degree under the one-to-many regime results from the interplay of two processes. On the one hand, a higher degree increases the proportion of closed triads in the network, fostering the extent to which one-to-many communication can produce cultural clustering and isolates. On the other hand, a higher degree also increases the share of the population to which an agent is directly exposed. The larger this share, the less likely it is that an agent disagrees with all network neighbors. The resulting cultural influence pushes the population towards more consensus, as already demonstrated by Axelrod. The combination of both processes generates a dynamic in which cultural clustering peaks at a degree of about 6, with lower levels of cultural clustering observed at both lower and higher degrees.

**4.2.4. Spatial Random Graphs.** Considering that both torus networks and the rewired ring networks are somewhat artificial network topologies, we also studied spatial random graphs, as these networks have been argued to mimic the structure of human social networks [39]. In particular, spatial random graphs exhibit many features of real social networks such as low tie density, short average geodesic distance, a high level of transitivity, a positively skewed actor-degree distribution, and a community structure [40]. We conducted a third simulation experiment to test whether the differences between one-to-many and one-to-one communication found with the torus networks also appear under these less controlled but more realistic conditions. Like in the previous simulation experiment, we assumed that agents are described by three features ( $F = 3$ ) that could adopt two traits ( $Q = 2$ ). We manipulated population size in the same way as in Section 4.2.1 and conducted 1,000 independent runs per experimental condition.

We initialized the network in two steps. First, all agents were randomly assigned two real numbers from the set  $[0, 5]$  that defined their position on a  $5 \times 5$  plane. Subsequently, we looped over all agents creating  $k$  ties probabilistically with agents with whom they did not share a tie yet. Whether a

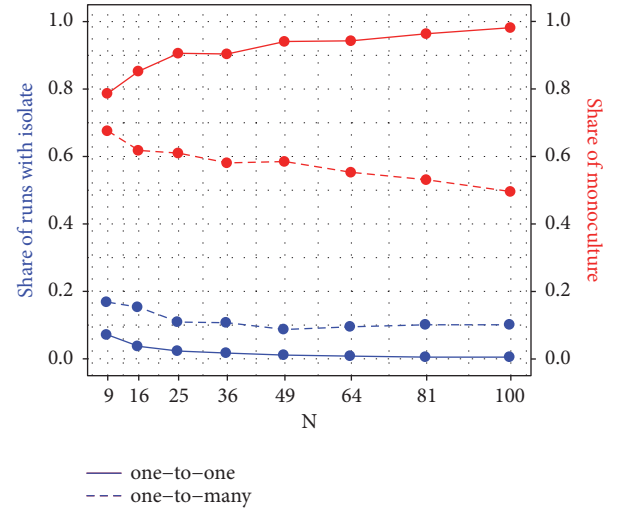


FIGURE 11: Effect of population size  $N$  on the share of runs with at least one isolate (blue lines), and share of runs characterized by monoculture (red lines) in a spatial random graph with  $F = 3$ ,  $Q = 2$ , 1,000 replications per condition.

tie between  $i$  and  $j$  was created depended on the Euclidean distance between the two agents on the plane ( $d_{ij}$ ) and the parameter  $\gamma$  that controls the strength of the relationship between distance and the probability to form a tie. We set  $k = 8$  such that each agent had a neighborhood of at least eight neighbors.<sup>6</sup> The probability that a tie was formed depended on the value of  $f(\gamma, d_{ij})$ , proportional to the sum of this function over all possible  $j$ 's, where

$$f(\gamma, d_{ij}) = \exp(-\gamma[d_{ij}]) \quad (5)$$

The resulting social networks are characterized by a transitivity value of 0.523, on average, which is slightly more transitive than the torus graph with Moore neighborhoods (transitivity is 0.429) that we studied in Section 4.2.1. Figure 11 visualizes how population size affected the share of runs ending in monoculture (red lines) and the share of runs where the population comprised at least one isolated



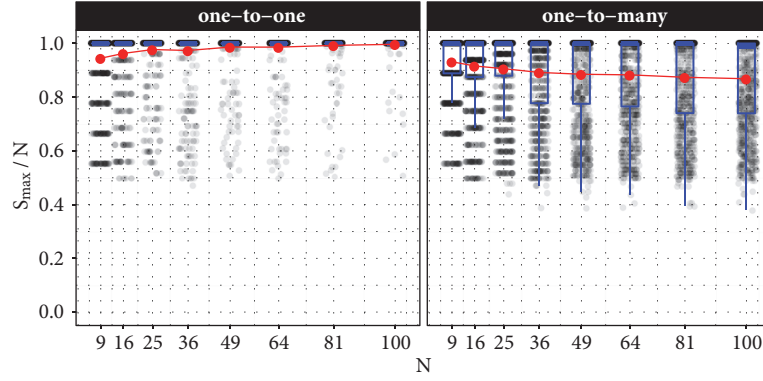


FIGURE 12: Homogeneity after convergence in a spatial random graph with  $F = 3$  and  $Q = 2$  by number of agents and communication regime. Boxplots are shown in blue and averages indicated with red marks. 1,000 replications per condition.

agent in equilibrium (blue lines). Figure 12 shows how the relative size of the biggest cultural subgroup was affected by population size and the communication regime. Both figures are markedly similar to the two corresponding figures for the torus networks, showing that our earlier findings are corroborated also when a more realistic network structure is assumed.

**4.2.5. Typical Simulation Runs.** Figure 13 shows one typical simulation run for each communication regime. Under Axelrod's original one-to-one regime (Figure 13(a)), one can see that the culture that eventually dominates does not diffuse from one strong cluster. In all snapshots the dominant culture is present in all regions of the network. For the lion's share of the total body of simulation events, about 1/3 of all attempted communication events result in a change of culture by an agent. In the last stage (between Snapshots 3 and 4), this rate drops to approximately 1/7 as the dominant cluster assimilates the last deviants.

The typical dynamics under one-to-many communication differ, as Figure 13(b) demonstrates. Between the outset and the second snapshot, the dynamics generate three clusters, each located in a distinct region. This happens at a high rate of about 1 cultural adjustment per simulation event.<sup>7</sup> As a population with three cultural subgroups can never be stable under  $Q = 2$ , dynamics continue until two cultural groups remain. The rate of  $s/t$  drops to 1/5 until converging to a situation with a majority cluster ( $N = 78$ ), one minority cluster ( $N = 21$ ), and one isolate. The isolate (located at the bottom right of the graph) has been locked inside the majority cluster from a very early stage and remains isolated from communication with other clusters throughout the rest of the run.

**4.2.6. Cultural Complexity.** The main innovation of Axelrod's model was to show how cultural diversity can emerge and persist despite relentless pressures on individuals to assimilate to cultural influence. Axelrod and many follow-up studies also demonstrated how, in the framework of this model, stable cultural clustering is a feasible outcome only

in a particular "sweet spot" in the parameter space in which the cultural space is not too complex, meaning that neither  $F$  nor  $Q$  are too large. If the cultural space consists of too many different features ( $F$ ), this increases the chances that neighboring agents happen to agree on at least one of them by random chance, exacerbating the emergence of cultural boundaries and thus promoting monoculture. If there are too many different traits per feature ( $Q$ ), it is unlikely that two neighboring agents happen to have the same trait at the outset, which precludes interaction between them and entails cultural anomie [9, 26].

We wanted to know whether our model can replicate these fundamental results of Axelrod's model under both communication regimes, to establish that, besides the differences we have shown, the two communication regimes generate consistent behavior. For the region where cultural clustering is feasible according to Axelrod's model, we wanted to know whether the larger degree of cultural isolation and cultural clustering for the one-to-many regime generalizes to a broader range of parameter values for  $F$  and  $Q$  than those we have used hitherto. For this purpose, we compared the two communication regimes under different assumptions about the complexity of the cultural space.

Figures 14 and 15 identify the region in which cultural clustering occurs both for Axelrod's original model and for the model with one-to-many communication. Our results show that clear differences between the communication regimes occur throughout the region in which Axelrod's original model navigates in between anomie and monoculture. In this region, the one-to-many regime produces more cultural isolation and more cultural clustering than one-to-one particularly when both the number of features is small ( $F = 3$  or  $F = 5$ ) and the number of traits is small or intermediate (depending on  $F$ ). With high  $F$  or high  $Q$ , the behavior known from Axelrod's original model is replicated also by the one-to-many version. In this region, the forces pushing towards monoculture or isolation largely overwhelm the distinct effects of the communication regime and strongly reduce the differences between them. Nevertheless, even in those conditions we find a consistent

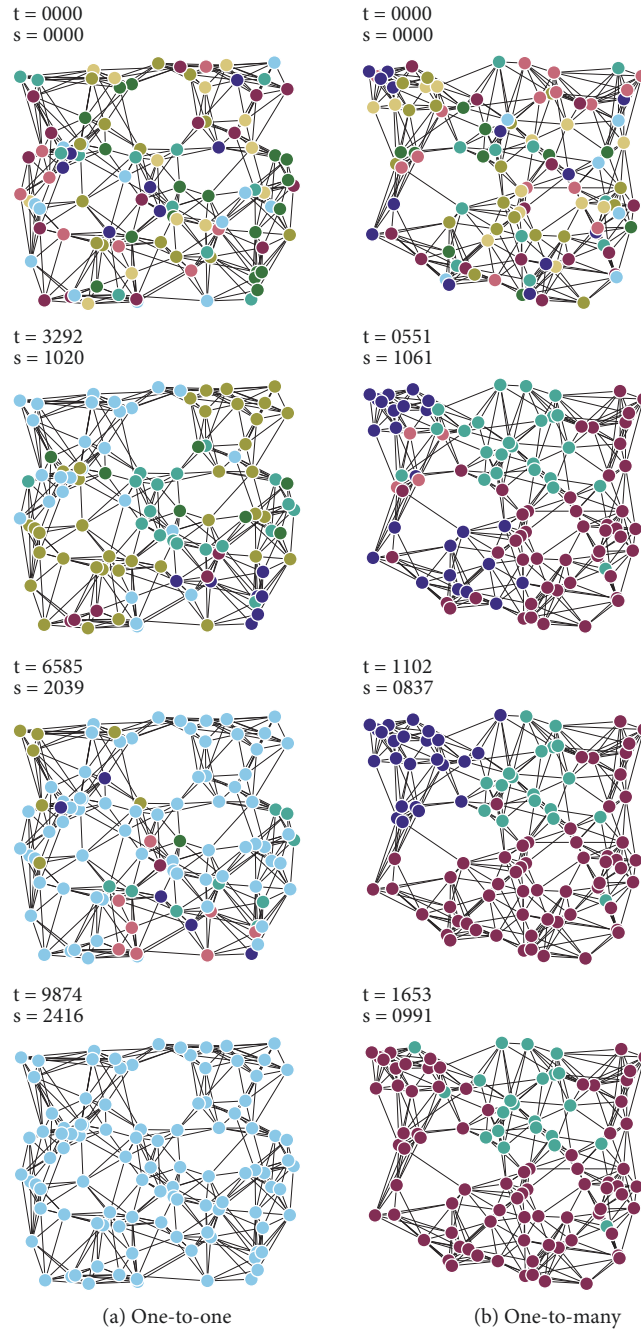


FIGURE 13: Typical runs under the two communication regimes for spatial random graphs with  $N = 100$ ,  $F = 3$ , and  $Q = 2$ . Every distinct combination of traits is visualized with its own unique color. The top graphs show the initial setup and the bottom graphs show the two populations in equilibrium. The remaining graphs visualize the distribution of cultural traits after 33% and 66% of the number of simulation events needed to reach equilibrium.  $t$  is the number of simulation events, and  $s$  is the number of events where an agent adjusted her set of cultural traits.

but very small difference in the expected direction: more cultural clustering and more isolates under the one-to-many regime. This supports our observation that one-to-many communication generates different influence dynamics than one-to-one communication in those areas of the parameter space where cultural diversity can be sustained at all under Axelrod's model.

## 5. Discussion and Directions for Future Work

Public debate about the role that online social networks, personalization algorithms, and fake news played in recent political events such as Brexit and the election of Donald Trump demonstrate that there is a need for a valid model of influence dynamics in online contexts. While the literature

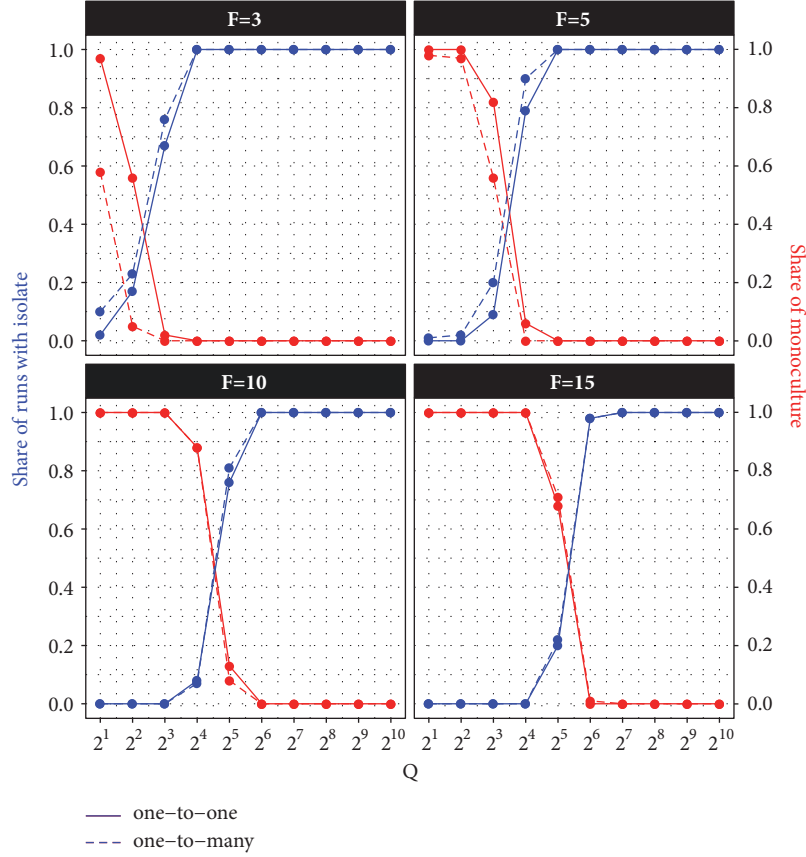


FIGURE 14: Effect of the number of features ( $F$ ) and traits per features ( $Q$ ) on the share of runs with at least one isolated agent in equilibrium (blue lines) and the share of runs ending with perfect monoculture (red lines). All simulations with a torus network with  $N = 49$  agents and 100 replications per condition.

already provides a rich arsenal of formal models, our analyses demonstrated that it can be misleading to readily adopt models developed for communication dynamics in offline worlds to the analysis of online contexts. In particular, we compared one-to-one communication, a communication regime implemented in many models of offline communication, with one-to-many communication which seems to be a more plausible representation of communication in online contexts such as blogs and online social networks like Twitter and Facebook. We reasoned that one-to-many communication fosters isolation and the emergence of cultural clusters, because an agent who happens to not be influenced by a message received from a network contact does not only fail to grow more similar to the source of the message. In addition, the agent also grows more dissimilar to those contacts of the sender who were influenced by the message and adopted the trait of the source. Building on Axelrod's cultural-dissemination model [9], we implemented one-to-many communication where a sender emits one message across his entire local network rather than just a single network contact. We started with a Markov-Chain analysis of a simple but tractable part of the parameter space ( $N = 4$ ,  $F = 3$ ,  $Q = 2$ ) and found support for our conjecture that one-to-many communication fosters the emergence of isolated individuals as well as polarization. Next, we conducted a series of simulation experiments to

demonstrate (1) that one-to-many communication fosters the isolation also in bigger populations, (2) that network transitivity fosters the emergence of isolated individuals and cultural clusters, and (3) that these findings hold for network topologies that mimic the structure of real social networks.

These findings add a new perspective to research on differences between online and offline communication. Earlier research was inspired by a psychological perspective and found that individuals are not affected by the physical appearance of their communication partners when communication is mediated by a computer [12, 13]. As a consequence, when communicating online individuals neglect the social roles associated with memberships in high or low status groups, which decreases intergroup conflict and fosters consensus formation. In contrast to this *within*-individual perspective, we focused on *between*-individuals effects, showing that differences between online and offline communication may not only arise from the fact that individuals behave differently when they communicate online or offline. We demonstrated that differences between online and offline communication can arise from differences in communication structure, because in many online settings individuals communicate to multiple receivers at the same time. This difference in the way communication is structured in many online settings

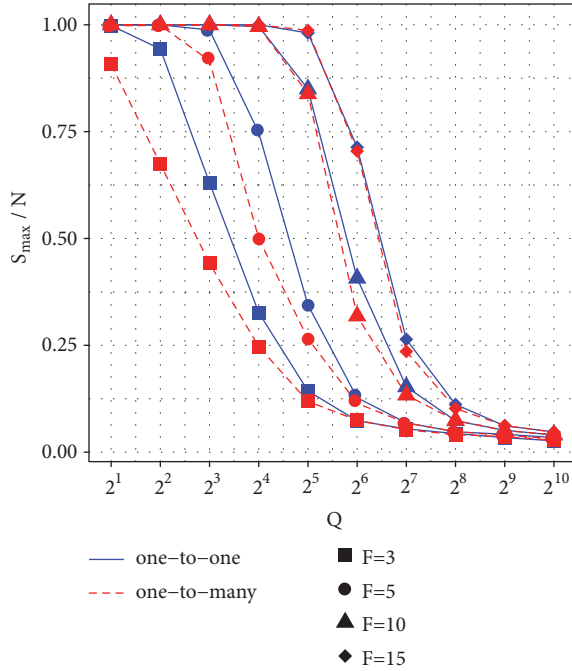


FIGURE 15: Effect of the number of features ( $F$ ) and traits per features ( $Q$ ) on the relative size of the biggest cultural cluster in the population. All simulations with a torus network with  $N = 49$  agents. Results are averaged over 100 replications per condition.

turned out to foster cultural isolation and clustering rather than consensus formation.

While our results support our conjecture that assuming one-to-one communication in models of online settings can lead to false conclusions, there is reason to expect that also the model that we studied may still deviate in critical ways from communication in real online settings. Future theoretical work should, therefore, explore further to what extent existing models can capture important features of online communication and which further model developments are needed for that purpose. We propose three possible directions.

First, a potentially important difference between Axelrod's model and our extension on the one hand and Internet communication on the other hand is that online network ties are flexible. On the one hand, intuition and earlier modeling work suggests that making networks dynamic will foster cultural diversity, as isolated agents and subgroups will cut off ties to their dissimilar network neighbors [30]. This should further decrease chances that isolates are influenced by former contacts. On the other hand, the Internet makes it easy to identify and connect to like-minded individuals even when they are geographically very distant [41]. This might allow isolated individuals and subgroups to join clusters that still communicate with individuals who are similar to their former connections and, thus, act as a bridge over the cultural divide. Given these competing intuitions, future research is needed to explore the conditions under which dynamic networks foster isolation under the one-to-many communication regime.

Second, future theoretical research should explore populations that are more heterogeneous. For instance, empirical research showed that the degree distribution of the Facebook graph is skewed [42, pp. 4], which suggests that some users may be more effective than others in spreading cultural attributes across the graph [43]. Future research should, therefore, study how variation in neighborhood sizes affects cultural dynamics. Furthermore, Internet users differ in their online activity. Research showed, for instance, that on Facebook politically active users emit more online content than users who are not politically engaged [44]. It is an open question, how these forms of heterogeneity affect isolation dynamics under the one-to-many communication regime.

A third important direction for future research is the study of one-to-many communication with alternative models of social influence. Unlike Axelrod's model, many alternative approaches represent cultural attributes on a continuous scale and not as distinct categories [8]. Many political opinions, for instance, tend to vary between extremes and are, thus, better described by metric scales. Models of continuous opinion dynamics can also capture more complex social-influence processes, such as gradual opinion-adjustments [45], negative influence exerted by too dissimilar sources [46], and the reinforcement of opinions when two actors communicate persuasive arguments that support each others' views [47]. Future research should explore whether and under what conditions assuming one-to-many communication alters the predictions of these models. We expect that the mechanism responsible for isolation and clustering under the one-to-many regime is activated also in models assuming continuous cultural attributes. If an actor refuses to be influenced by a communication partner, he does not only refuse to grow more similar to this actor. In addition, the actors grows more dissimilar to those joint network contacts that were influenced and, therefore, were pulled closer to the sources of communication.

Another important avenue of future research is to empirically test our theoretical prediction that one-to-many communication fosters isolation and cluster formation. We propose a three-step design that resembles the structure of the theoretical analysis in this paper. First, we propose to study the minimal case that we explored with analytical tools in a computerized laboratory environment, with four human subjects discussing their stance on three binary issues. In this setting, one can manipulate whether subjects communicate in pairs (one-to-one) or emit messages to all participants at once (one-to-many). With this experimental design, one can also test our theoretical prediction against the finding from the psychological literature that computer-mediated communication fosters consensus formation in demographically diverse groups. In particular, it would be interesting to test whether the integrating effects of computer-mediated communication are stronger or weaker when communication is implemented according to the one-to-one or to the one-to-many regime. Second, laboratory experiments are also a fruitful approach to compare the two communication regimes in bigger populations. Our theoretical analyses suggest that these experiments should focus on social networks characterized by high clustering and settings with relatively



TABLE 3: Classes and their number of configurations for the  $N = 4$ ,  $F = 3$ ,  $Q = 2$  model.

| Class                             | Number of states included in the class | Share of states included in the class |
|-----------------------------------|--|---------------------------------------|
| C-C-C ( <i>consensus</i> )        | 8                                      | .002                                  |
| 22-C-C                            | 72                                     | .018                                  |
| 22-22-Cs                          | 72                                     | .018                                  |
| 22-22-Cns                         | 144                                    | .035                                  |
| 22-22-22s ( <i>polarization</i> ) | 24                                     | .006                                  |
| 22-22-22ss                        | 144                                    | .035                                  |
| 22-22-22ns                        | 48                                     | .012                                  |
| 13-C-C                            | 96                                     | .023                                  |
| 13-13-Cs                          | 96                                     | .023                                  |
| 13-13-Cns                         | 288                                    | .070                                  |
| 13-13-13s ( <i>isolation</i> )    | 32                                     | .008                                  |
| 13-13-13ss                        | 288                                    | .070                                  |
| 13-13-13ns                        | 192                                    | .047                                  |
| 13-22-C                           | 576                                    | .141                                  |
| 13-13-22s                         | 288                                    | .070                                  |
| 13-13-22ss <sup>a</sup>           | 288                                    | .070                                  |
| 13-13-22ns <sup>b</sup>           | 576                                    | .141                                  |
| 13-22-22s                         | 288                                    | .070                                  |
| 13-22-22ns                        | 576                                    | .141                                  |
| Total                             | 4,096                                  | 1.000                                 |

<sup>a</sup> The outliers on the 1-3 split features are members of the same group on the 2-2 split feature; <sup>b</sup> the outliers on the 1-3 split features are members of different groups on the 2-2 split feature.

small cultural complexity, as the differences between the two regimes were strongest under these conditions. Third, one might try to test macro predictions in the field, comparing influence dynamics in online communities with different local network structures. Contrary to intuition, our results suggest that the chances that individuals turn culturally isolated are higher when their local network is characterized by high transitivity.

There is strong public and scholarly interest on the effects of communication in online worlds. On the one hand, our results illustrate that the formal analysis of abstract models can contribute to exploring the complexity of online communication systems. On the other hand, our findings also show that pundits, experts, scholars, political decision makers, and also developers of online communication systems need to be very careful when reasoning about the consequences of online communication. Being based on modeling work and empirical studies focused on offline settings, the current scientific state of the art does not yet allow drawing reliable conclusions about the effects of online communication on societal processes of consensus formation and opinion polarization.

## Appendix

### A. Classes in the $N=4$ , $F=3$ , $Q=2$ Model

Table 3 presents the number and proportion of unique states within each class.

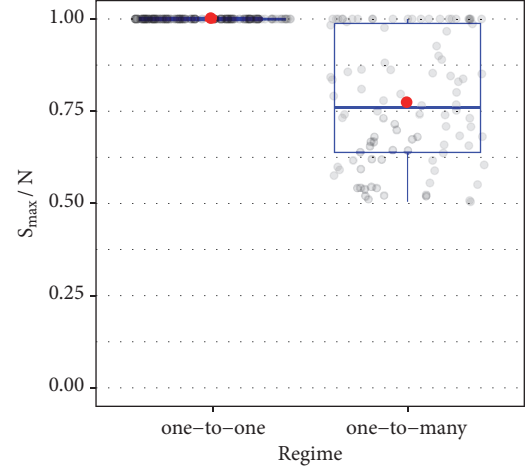


FIGURE 16: Homogeneity after convergence in a torus network with  $N = 900$ ,  $F = 3$ , and  $Q = 2$  by communication regime. Boxplots are shown in blue and averages indicated with red marks. 100 replications per condition.

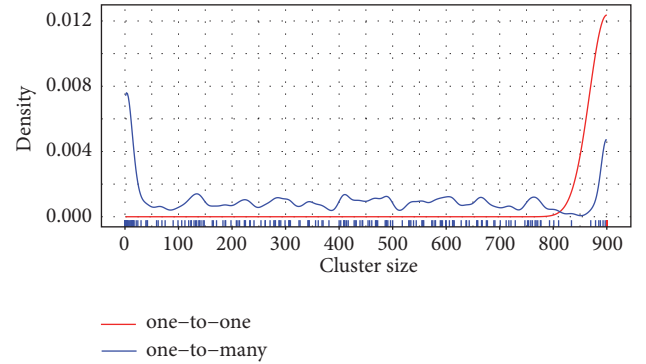


FIGURE 17: Density and rug plot of cluster sizes after convergence in a torus network with  $N = 900$ ,  $F = 3$ , and  $Q = 2$  by communication regime. 100 replications per condition.

### B. Replication with Large Populations

In Section 4.2.1, we studied the effect of population size, conducting simulations with populations of up to 100 agents. In addition, we also analyzed populations of 900 agents ( $30 \times 30$  grid), conducting 100 independent replications per communication regime. Under the one-to-one interaction regime all replications ended in complete homogeneity. Under the one-to-many interaction regime only 23 replications ended in monoculture, and of the remaining 77 replication runs 26 generated at least one isolate.

Figures 16 and 17 compare model outcomes under the one-to-one and the one-to-many communication regimes. Both figures show that the results found with smaller population are obtained also in substantially bigger networks: one-to-many communication generates more cultural isolation and diversity than one-to-one communication.

## Data Availability

No empirical data were used for this study.

## Disclosure

An earlier version of this paper has been presented at the XXXVIII Sunbelt conference.

## Conflicts of Interest

The authors declare that they have no conflicts of interest

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## Endnotes

1. Nonconsensus features of the same type are symmetrical if the agents who agree on one feature also agree on the other. If there are three nonconsensus features of the same type and only two features are aligned, we label this class semi-symmetrical. In principal, the alignment on features of different types does not matter for state classification, with the exception of the 13-13-22 semi-class where the two 1-3 split features are not symmetrical. Here we label the class semi-symmetrical if the outliers on the 1-3 split features are members of the same group on the 2-2 split feature and non-symmetrical if they are not.
2. Consensus is inevitable in the red classes because there is at least one feature on which the agents have reached consensus. As a consequence, all pairs of neighbors will always exert influence on each other with a positive probability. This will eventually generate consensus. Likewise, it is not possible that a state of consensus on one or more features can be left.
3. The transition probabilities for going from the 13-13-22s to the 13-13-13s class are  $p = .33$  under one-to-many communication and  $p = .11$  under one-to-one communication.
4. Axelrod first used the smaller "Von Neumann" neighborhoods but also tested the robustness of his results with a "Moore" neighborhood identical to the one we employ.
5. Besides manipulating transitivity, the implemented method also creates between-node heterogeneity in their network centrality and decreases the average path length in the graph. This might, in turn, affect the dynamics of our model. However, due to the inherit interrelatedness of network descriptive statistics there is no method of manipulating transitivity without changing other aspects of the network structure.

6. Every  $i$  formed eight ties, but a  $j$  that already possessed eight ties was not excluded from the set of  $i$ 's potential neighbors.
7. It is not possible to compare these rates between communication regimes without postprocessing. As a sender's whole neighborhood (of 8 or more agents) can be influenced in a single simulation event in the one-to-many model, a conservative approximation could be made by dividing the number of successful communication events over the number of iterations times 8. However, only the neighbors for whom  $0 < \text{similarity}_{ij} < 1$  can be influenced, and this number varies locally as well as over time.

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